The AIRS Humidity-Based Prediction System for Seasonal Influenza

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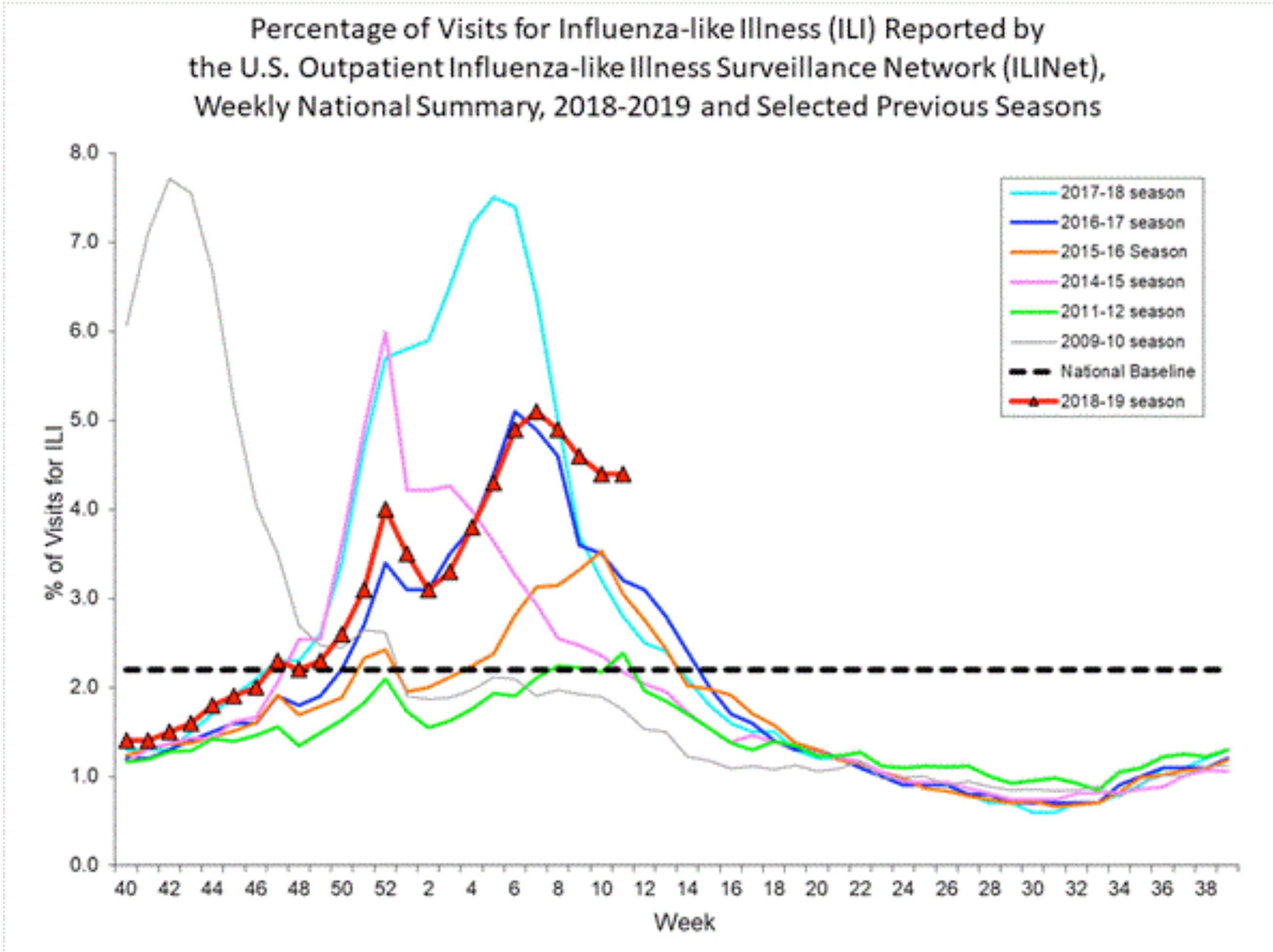
US Influenza Seasons

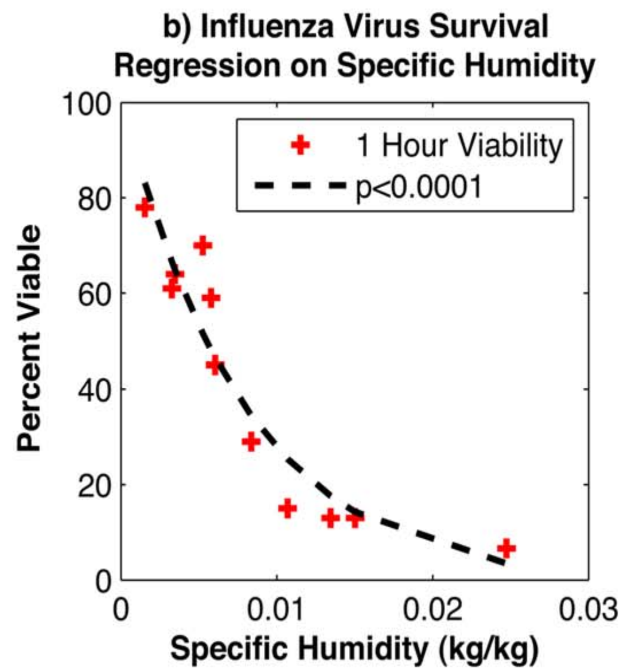


www.cdc.gov

- Influenza generally peaks in the winter
  - although the exact timing and strength of peaks varies
- Why is this?

Humidity & Influenza Seasonality

- There is evidence for specific humidity conditions as an important driver of the seasonal behavior of influenza outbreaks (in temperate regions)
  - Low absolute humidity associated with high influenza activity
  - In lab experiments (transmission and survival of virus as a function of humidity)
  - Using climate and influenza data records
  - Using epidemiological models



Shaman et al. (2010)

- Possible mechanisms
  - Drying of mucous membranes
  - Humidity effects on droplet sizes and travel range
  - Increased survival times for the virus

- Both absolute and relative humidity tend to be low indoors in the winter
  - Indoor temperature is controlled, humidity usually not

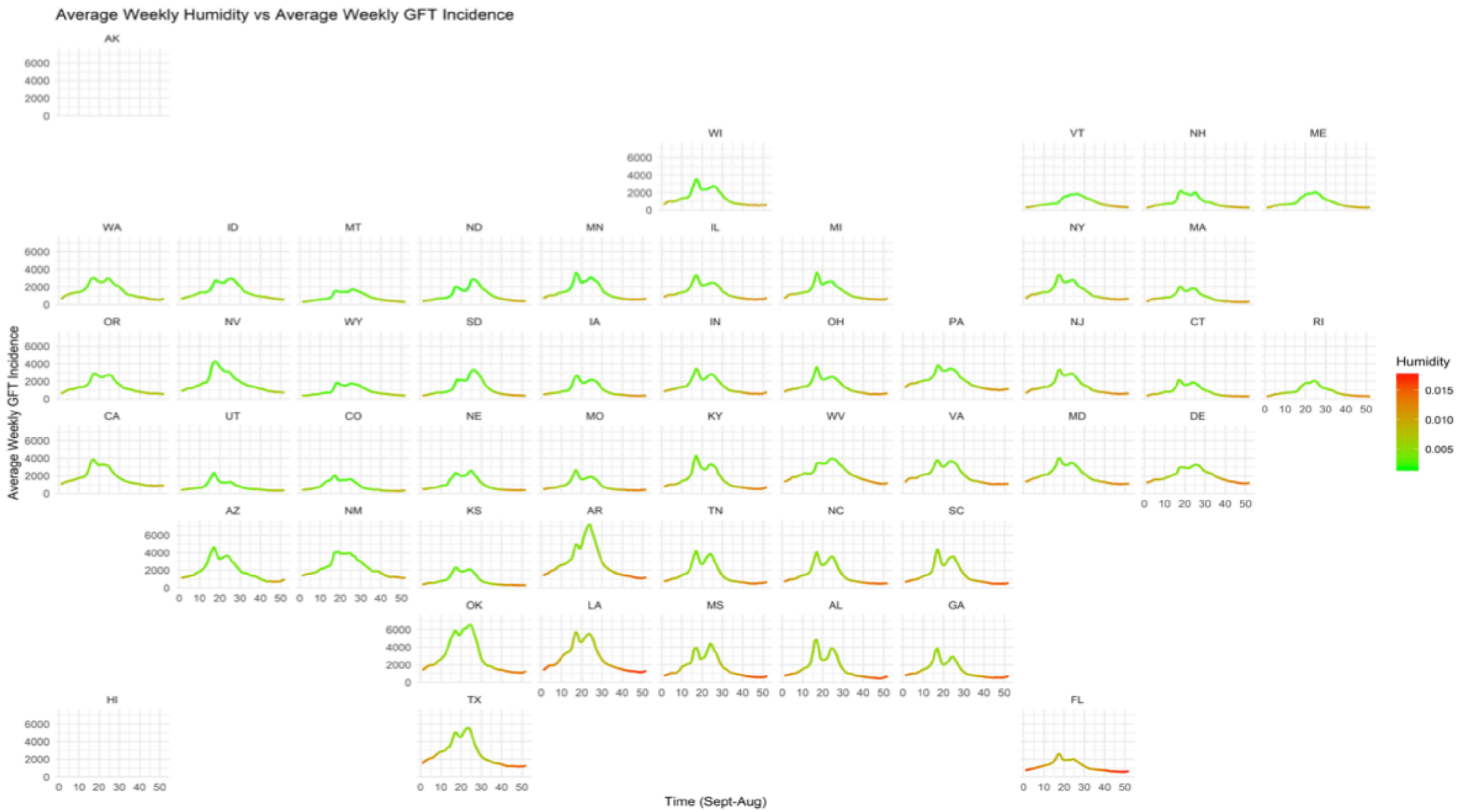
Value of Influenza Forecasts

- The Center for Disease Control and Prevention (CDC) now encourages and collects external US flu forecasts from a few models

- CDC website: **How can flu forecasts be used prior to and during outbreaks?** The potential uses of flu forecasts extend beyond communication, both in seasonal and emergency situations. Flu forecasts can potentially be used to prepare for and prevent illness, hospitalization, and death, as well as the economic burden, experienced during the epidemic. When forecasts accurately predict flu activity, the ability to more effectively plan for public health responses to seasonal flu epidemics and future influenza pandemics is possible. Flu forecasts can inform messaging to health care providers regarding influenza vaccination and antiviral treatment for patients. Forecasts can also help to prepare for an influx of illnesses and hospitalizations, potentially helping inform the distribution and placement of health care staff and treatment resources. Finally, forecasts can be used to guide community mitigation strategies, such as school closures.

Humidity & Influenza

- To make use of humidity-flu relationships in a forecast model, we need to characterize it at various levels (city/state/region)

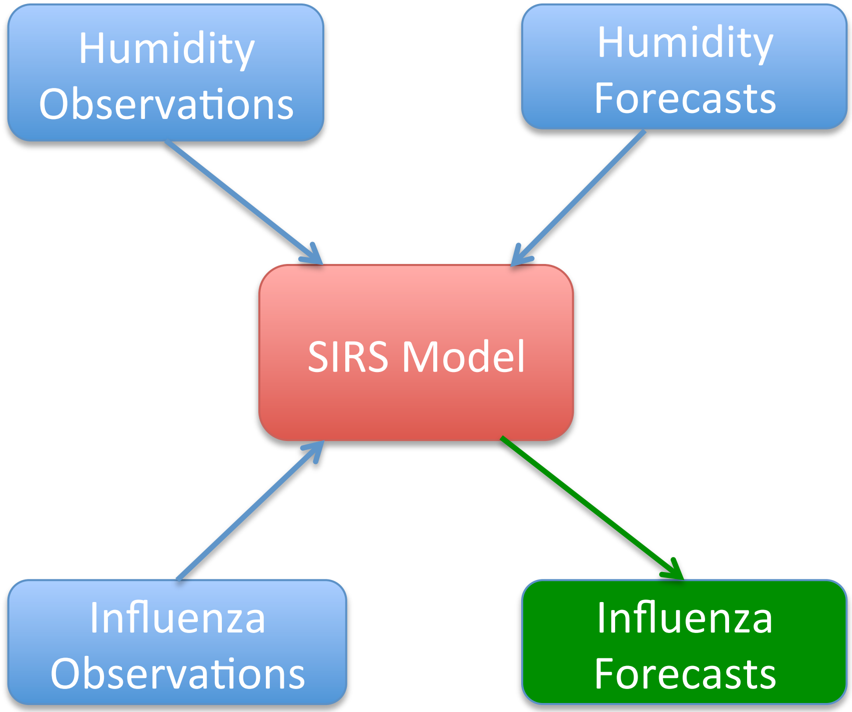


- Map of average flu seasons across US states, with average humidity color coded
  - time series of flu activity from Google Flu Trends, averaged over 2003-2015
  - AIRS weekly near-surface H_2O mass mixing ratio, averaged over 2003-2015

AIRS-Flu System Overview

- Daily updating most recent values for near-surface H_2O mixing ratio, AIRS level 3 data (v6)

- NCEP forecasts for near-surface humidity



- Influenza data assimilated

- The output is the number of infected and susceptible people in a population (city/state/region)

- From the Center for Disease Control (CDC) or LACDPH:
  - Regional, weekly surveillance records for the proportion of doctor's visits for influenza-like illness (ILI)
  - Combined with lab virology results for the percentage of influenza positive samples
  - Imperfect estimates of flu activity
  - Available with 1-2 weeks lag time
  - Incorporated with weights to make analysis and re-initialize the model

SIRS Model

$$\frac{dS}{dt} = \frac{N - I - S}{L} - \frac{\beta I S}{N} - \alpha$$

$$\frac{dI}{dt} = \frac{\beta I S}{N} - \frac{I}{D} + \alpha$$

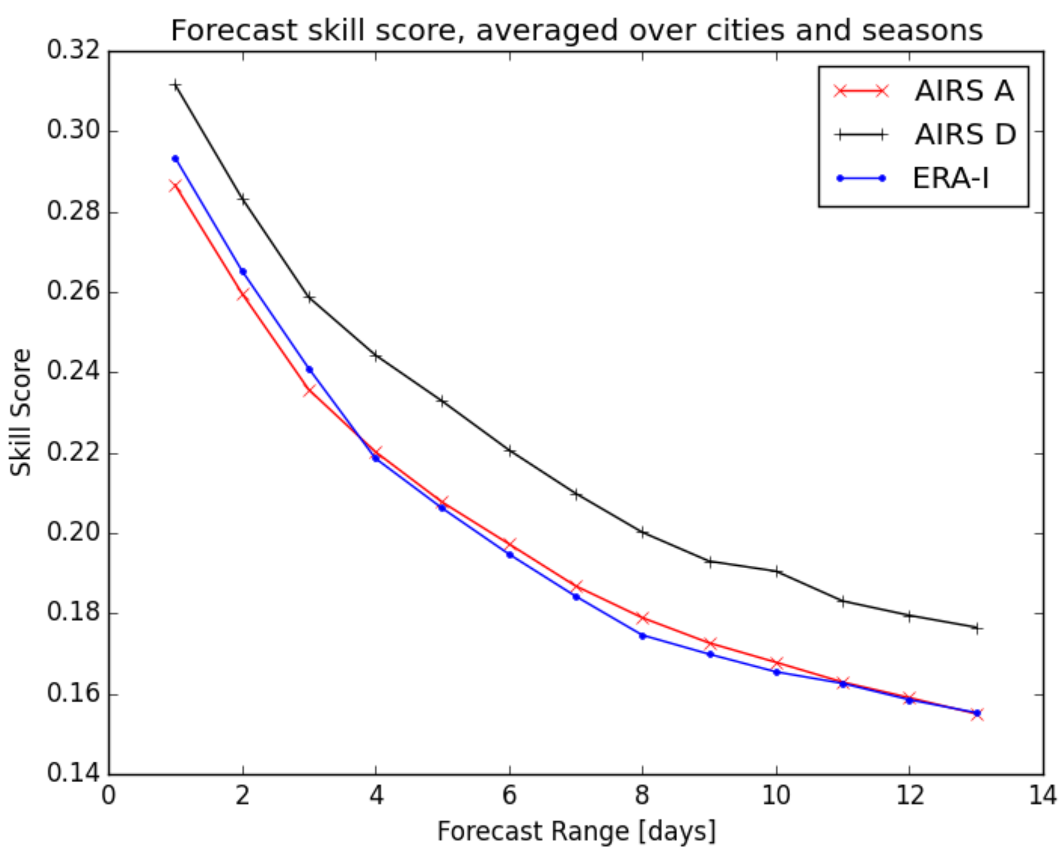
Specific humidity

$$\beta = \frac{R_0}{D} = \frac{1}{D}[R_{0min} + (R_{0max} - R_{0min})\mathrm{e}^{aq}]$$

N	Population size
S	Susceptible persons
I	Infectious (= infected) persons
L	Average immunity duration
D	Mean infectious period
α	Rate of (travel-related) import of virus into model domain
β	Contact rate
R_0	(Daily) basic reproductive number
a	(Negative) coefficient in contact rate exponential
q	Specific humidity

Tests with Different Sources of Humidity Data

- Hindcasts were performed for multiple seasons (2005-2015) and US cities (21 large cities)
- Everything was fixed except varying the source of humidity data driving the model (AIRS and ERA-Interim reanalysis)
- Skill score is higher when using AIRS nighttime humidity data

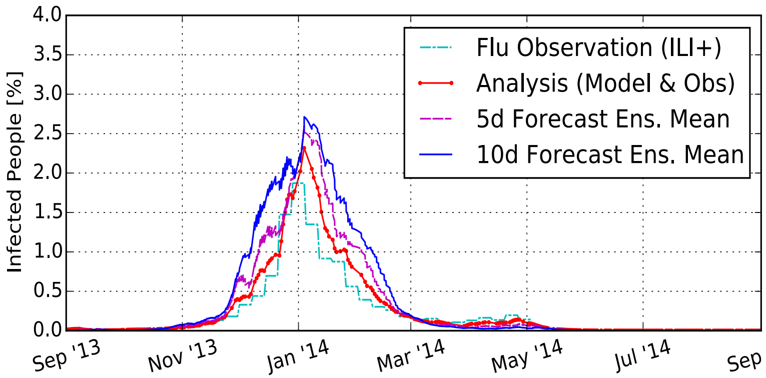


Thrastarson & Teixeira (submitted to Met Apps)

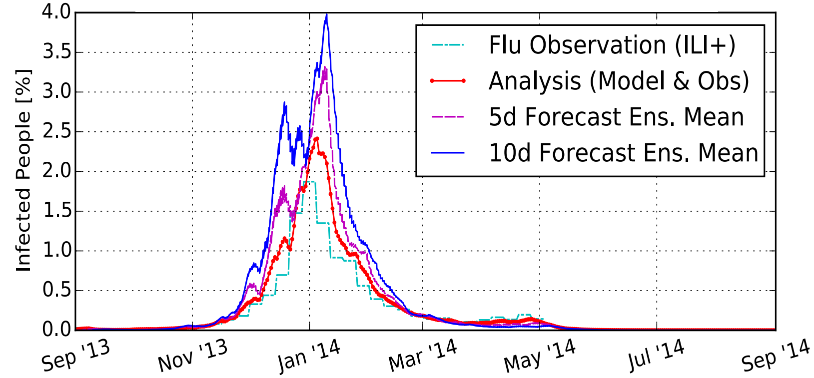
Effects of Humidity

Results for Chicago 2013-2014 with different (AIRS-A vs ERA-I) humidity sources

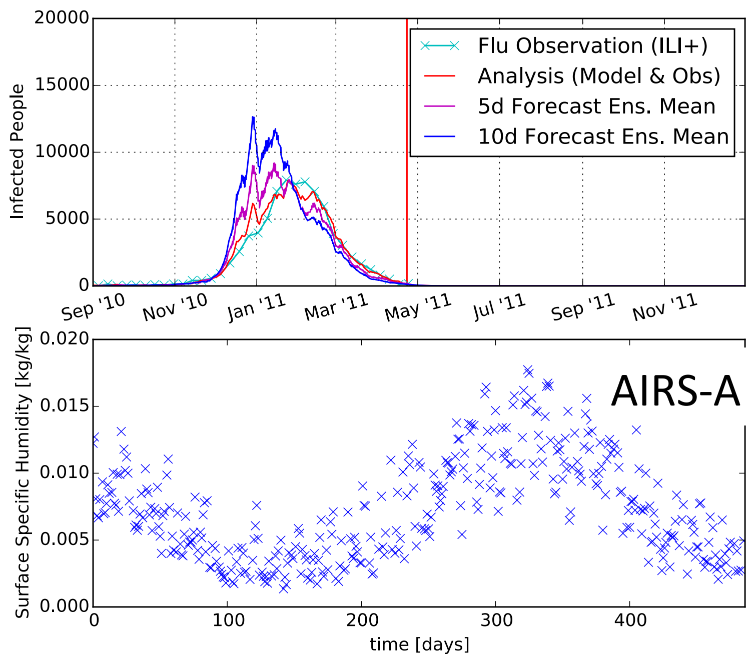
(a) Run with AIRS-A data

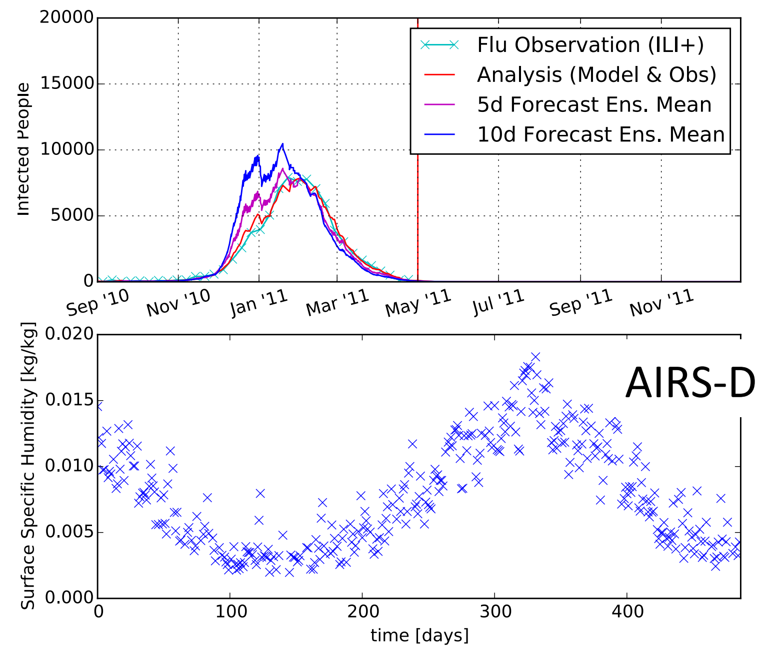


(b) Run with ERA-Interim data



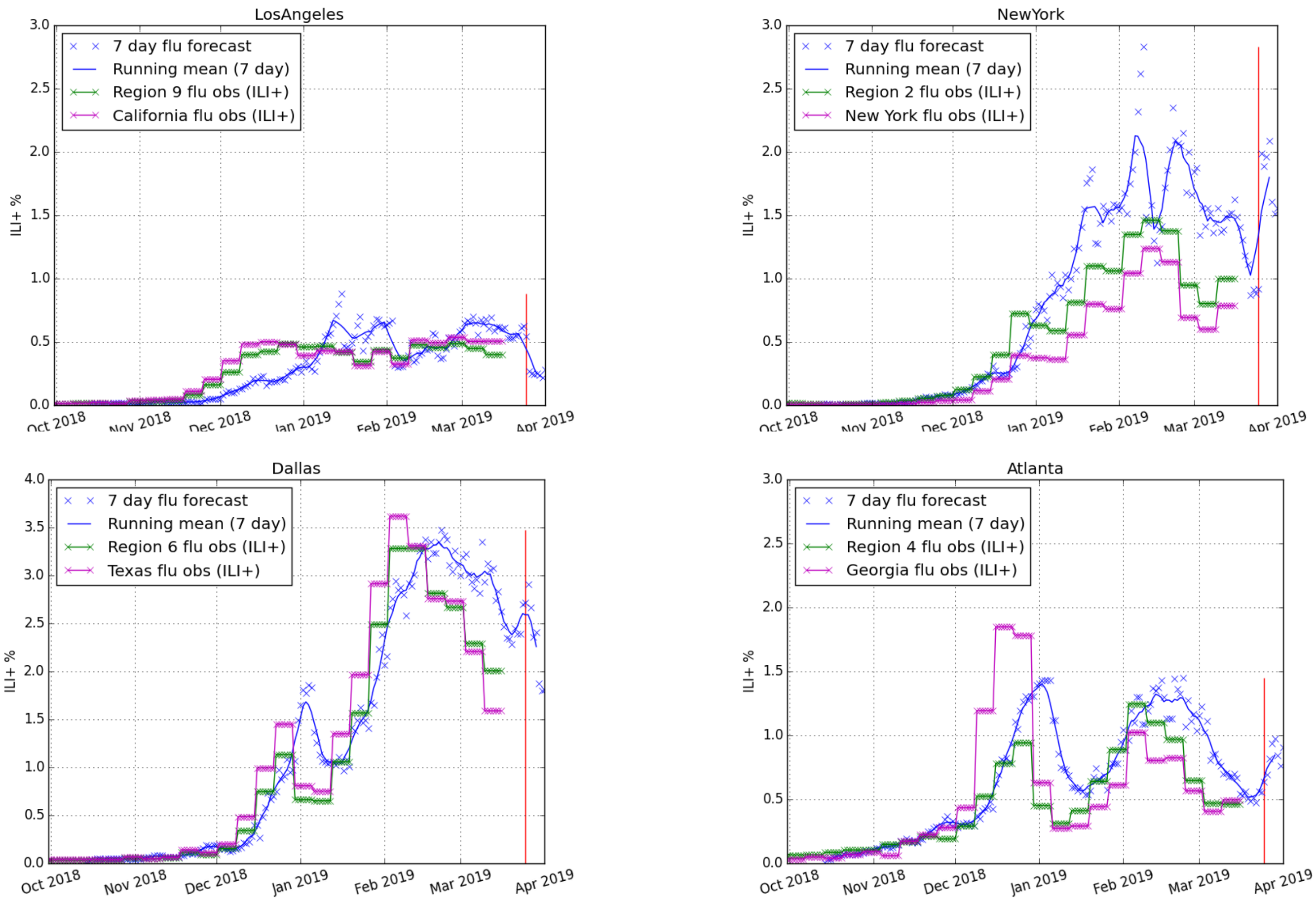
Results for Washington DC 2010-2011 with different AIRS (Asc vs Desc) humidity sources





2018-2019 Season – US Cities

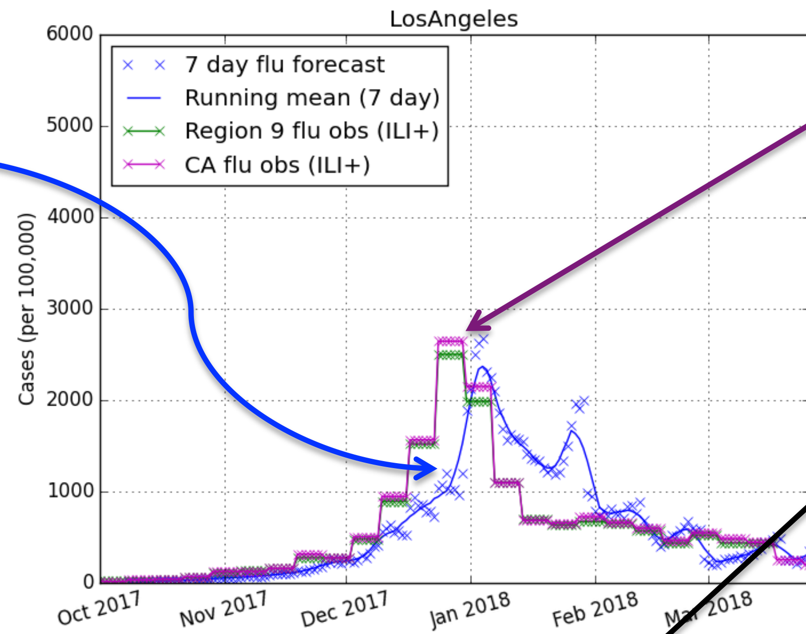
- Real-time forecasts run for three seasons
- Results shown for the 2018-2019 season in four US cities.



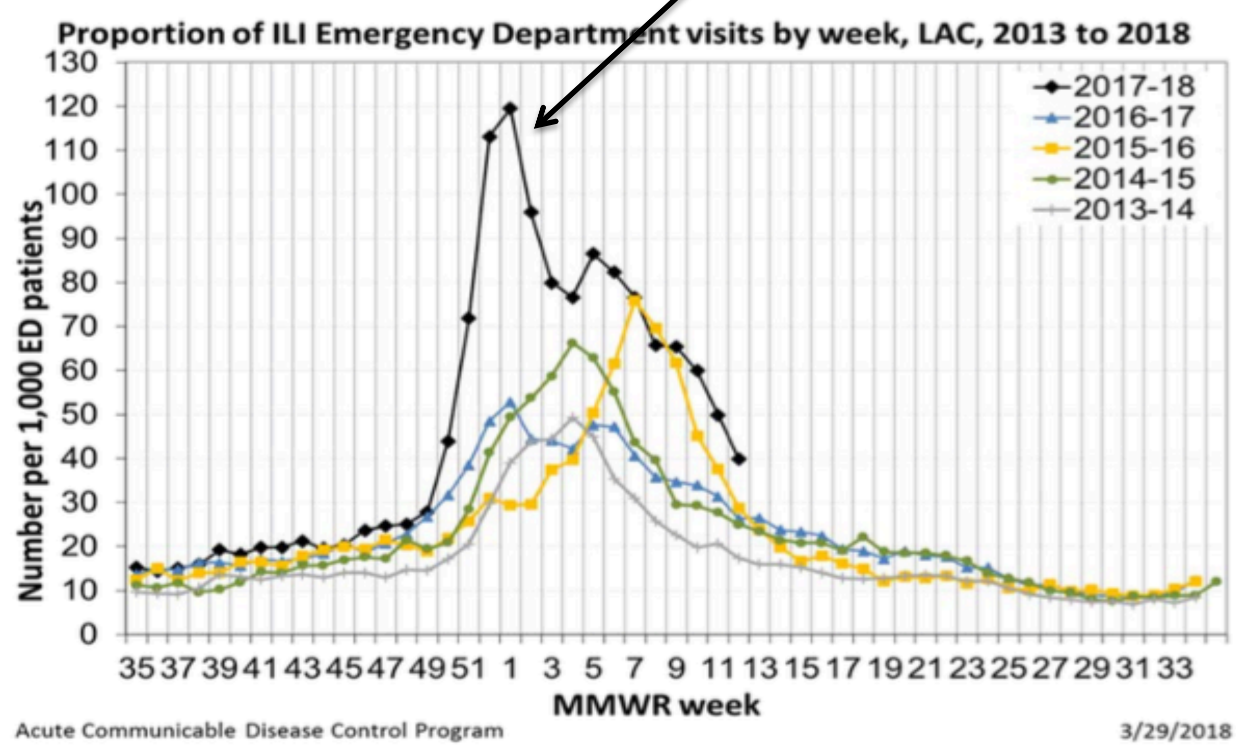
7 Day forecasts are shown in as blue crosses (ensemble mean of model results from 7 days prior). The blue line is the 7 day running mean of the forecasts. Here, previous seasons' results have been used for calibration. The red line is the latest 'launch date' for forecasts. ILI+ flu 'observations' in green at the regional level, and in magenta at the state level.

Los Angeles: 2017-2018

- Flu forecast system captures double peak (not present in assimilated data)
- According to LA CDPH[1]: if forecast of 2nd peak is available, even 1-2 weeks in advance, that would be very useful
- We are working with LA CDPH to test our system in operational context



- Only *regional* data was available for assimilation
- *CA* dominates Region 9
- *LA County* data was available afterwards for comparison



[1]LACDPH: LA County Dept of Public Health

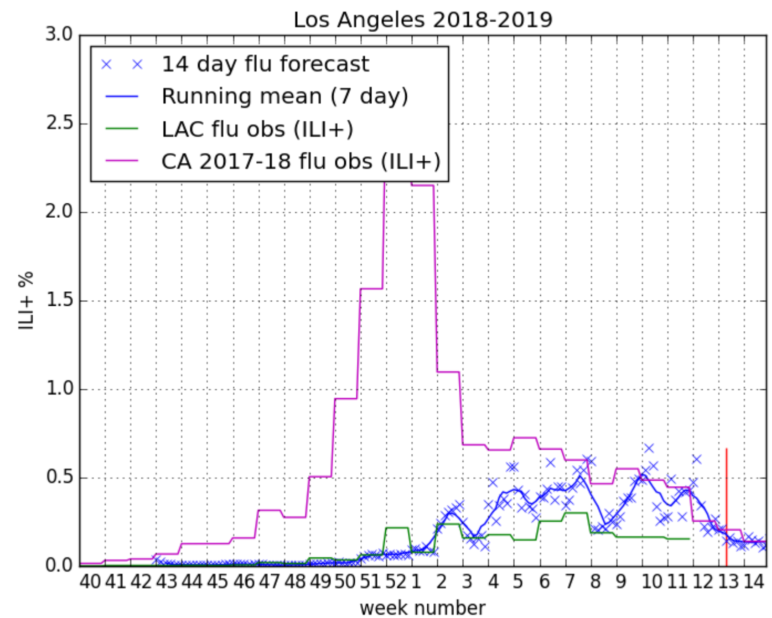
Collaboration with LACDPH

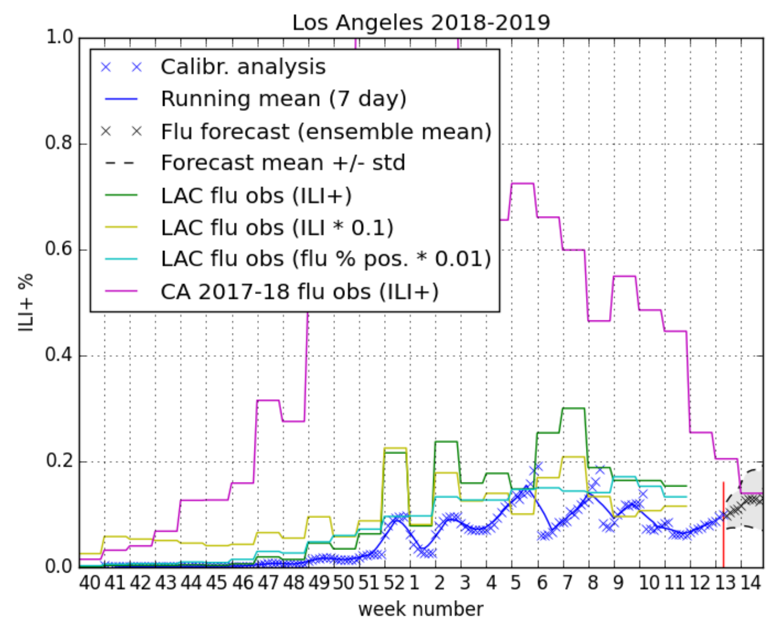
- Collaboration with LA County Dept of Public Health (LACDPH)
  - LACDPH provides local flu data
  - We provide flu forecasts in a mock trial
  - Regular ongoing communication on results and ways forward

- Some of the things addressed and learnt over the season:
  - We have gained insights into LACDPH's role for seasonal influenza
  - And how influenza prediction could potentially help
  - What is important for them and what not (relative trends can be valuable even when exact numbers aren't reliable)
  - Multiple iterations on the presentation of forecast results
  - Insights into changes, timing and updating of the surveillance data that can have strong effects on forecasts
  - Ideas on how to mitigate some of the limitations of the surveillance data (modified weighting depending on total counts)
  - Learning about and using different surveillance data sources (e.g. SoCal) with different characteristics
  - Ideas on further studies (effects of reporting lags, using vaccination efficiency data)

Flu forecasts - LA County data (2018-2019)

- Surveillance data assimilated and compared to are for LA County, both ILINet and % flu positive lab data.
- The upper plot shows the updated collection of 14 day forecasts over the season, to give an idea how the model has been doing compared to the surveillance data.
- Much weaker season than the last one
- Relatively prolonged season (as last season)
- The lower plot shows the latest best estimates for the following two weeks, along with different observational measures, as we have been communicating with LA County Dept of Public Health.



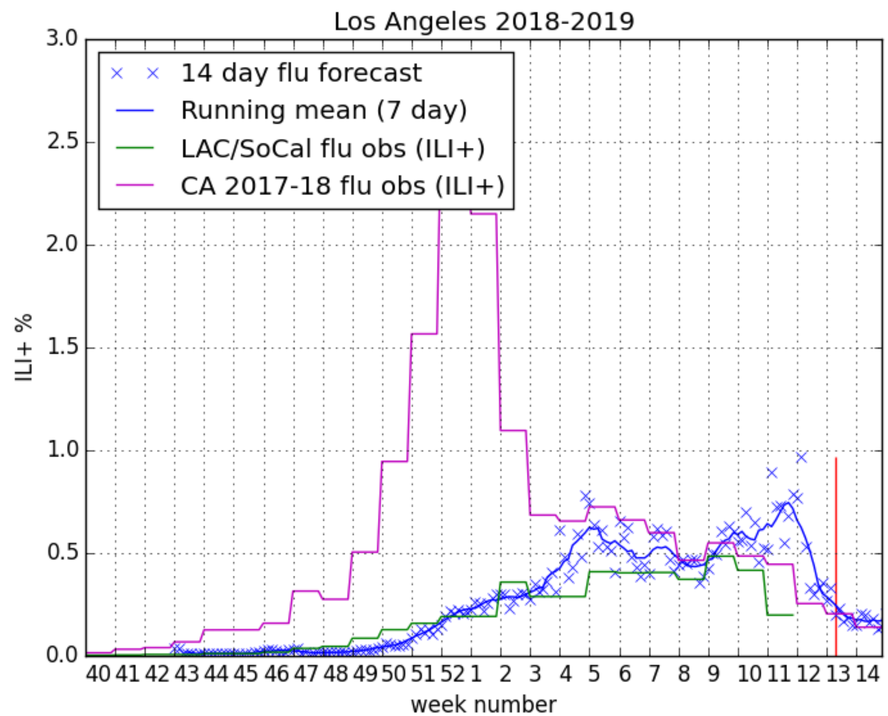


Flu forecasts - LA County & SoCal data

- Surveillance data assimilated and compared to are ILI for Southern California (upper + lower region) and % flu positive lab data from LA County providers.

- The plot shows the updated collection of 14 day forecasts over the season

- The model & observations appear more similar when (possibly more reliable) SoCal data is used rather than LA County ILI



Summary & Ongoing Work

- Near-surface humidity plays a critical role in influenza epidemics
- AIRS near-surface humidity is a key component of a quasi-operational (produced daily) influenza prediction system
- The system has been applied to make hindcasts for multiple previous seasons and real-time forecasts for the past three seasons, capturing fairly well overall trends (e.g. relatively severity of seasons) and timings
- Engagement with potential operational users
  - Trial with LA County Dep. Public Health has been fruitful, with many lessons and ideas
  - Working to be part of CDC's forecasting network
  - Global nature of AIRS data and weather forecasts offers possibility of extensions to other regions of the world (e.g. South Africa)

Acknowledgements

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